Transit-Centric Smart Mobility System for High-Growth Urban Activity Centers: Improving Energy Efficiency through Machine Learning

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Overview

Timeline

- Start: October 2020
- End: December 2023
- Modification: 3 months delay of two researchers and 8 months delay of the other two due to foreign national processing (FNP)
- 5% complete

Barriers

- Underdeveloped transit systems cannot meet the travel demand of high-growth urban areas.
- Short-term and long-term transit ridership cannot be predicted accurately.
- The transit system is vulnerable to system disruptions and unresponsive to the real-time dynamics of travel demand.

Budget

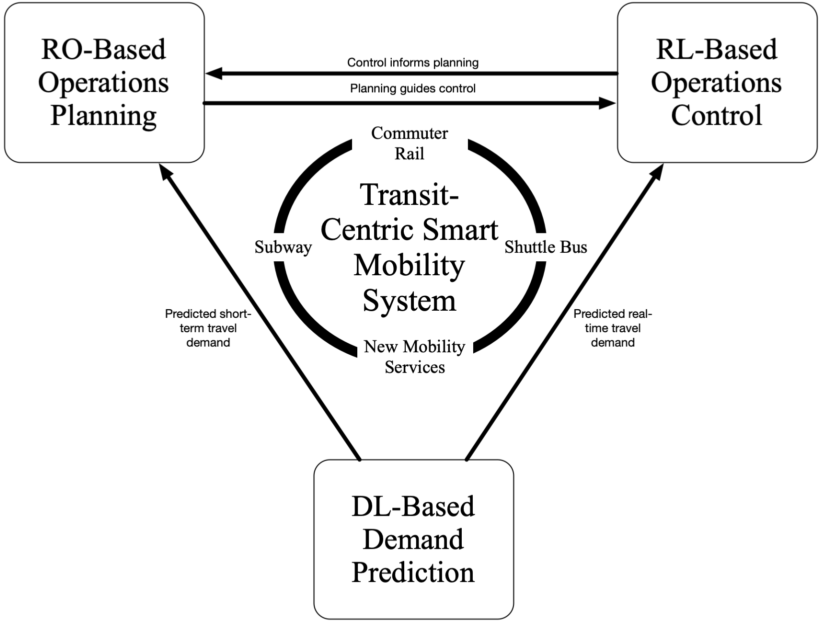
- Total funding: $1.75 Million
- Budget period 1: $499,945

Partners

- Research partners: Northeastern University; National Renewable Energy Laboratory.
- Transit partners: Massachusetts Port Authority; Massachusetts Bay Transportation Authority; Chicago Transit Authority.

Relevance – Achieve Three Main Objectives

- **Objective 1.** Designing a Transit-Centric Smart Mobility System (TSMS) that is adaptive to changing demand patterns, resilient to system disruptions, and responsive to real-time conditions.
- **Objective 2.** Building the Integrated TSMS with the state-of-the-art technology, including robust optimization (RO), reinforcement learning (RL), and deep learning (DL)
- **Objective 3.** Deploying operations control and demand. predictions in real-world experiments (Chicago and Boston) and large-scale simulations.



Project framework

Relevance – Achieve Broad and Specific Impacts

Broad Impacts

- Improving transit service quality, ridership, and energy efficiency, measured by NREL's Mobility-Energy-Productivity (MEP) metric.
- Advancing technology transfer to transit operators and enhancing US industry practices in terms of mobility and energy efficiency

Specific Quantitative Impacts

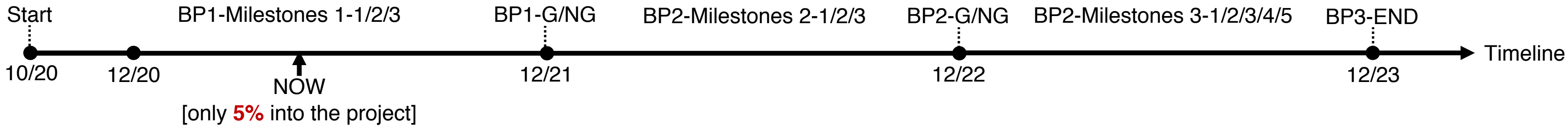
Field Experiments

- ≥ 5% reduction in passenger waiting and riding time for the specific routes in the field experiments
- ≥ 8% increase in predictive performance in spatiotemporally detailed models for transit mode share

Simulations

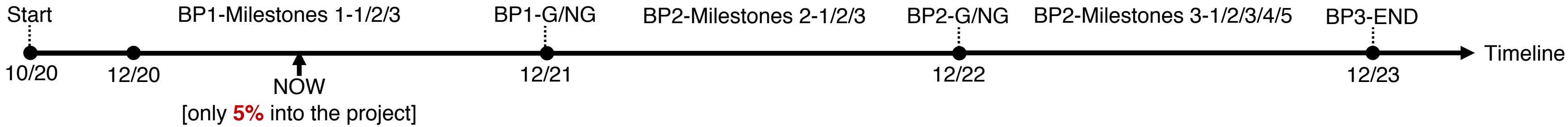
- ≥ 5% increase in transit mode share
- ≥ 3% increase in energy efficiency

Approach – Timeline and Go/No-Go Points



Budget Period	Start/End Date	Go/NG Points	Description
1	10/01/20 – 12/31/21 (3~8 months' delay due to FNP)	Completion of Core Technology Modules	• Transit operations planning, control, and demand prediction modules have functioning interfaces. • Documenting the passenger waiting and riding time and predicted ridership as the output metrics • Improving upon the baseline performances by ≥3% in all four scenarios.
2	01/20/22 – 12/31/22	Completion of Pilot Experiments	• Detailed implementation plans for full-scale field experiments are prepared. • At least ≥5% reduction of passenger waiting and riding time and ≥5% improvement of predictive performance in the completed pilot experiments.
3	1/1/2023 – 12/31/2023	Impact Communications Complete	• Success is evaluated by comparing results to the expected ≥5% reduction of passenger waiting and riding time and ≥8% improvement of predictive performance in experiments. • Impact of the technologies is evaluated by comparing to the expected ≥5% improvement of transit ridership and ≥3% improvement of energy efficiency in simulations.

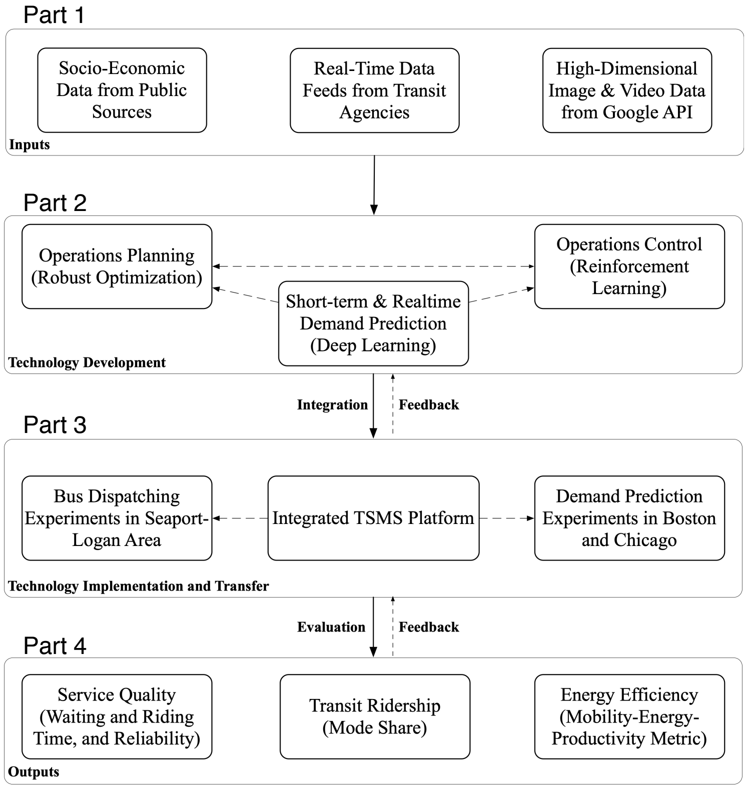
Approach – Timeline and Milestones



Budget Period	G/NG	Milestones	Targeting Objectives	Completion Status
1	Completion of Core Technology Modules	• M1-1: Operations Planning and Control Modules	OBJ1,2	**3%**
		• M1-2: Demand Prediction Module	OBJ1,2	**12%**
		• M1-3: Completion of Data Collection	OBJ1,2	**12%**
2	Completion of Pilot Experiments	• M2-1: Pilot Operations Control Intervention	OBJ1,3	NA
		• M2-2: Pilot Demand Prediction	OBJ1,3	NA
		• M2-3: Completion of Integrated Simulation	OBJ1,2	NA
3	Impact Communications Complete	• M3-1: Full Operations Control Experiments	OBJ1,3	NA
		• M3-2: Full Demand Prediction Experiments	OBJ1,3	NA
		• M3-3: Success Measures in Field Experiments	OBJ1,3	NA
		• M3-4: Success Measures in Large-Scale Simulations	OBJ1,3	NA
		• M3-5: Impact Communications Complete	OBJ1,3	NA

Approach – Four Steps

Part 1. Inputs - data collection: [Objectives 1,2]
Part 2. Technology development - three modules: [Objectives 1,2]
Part 3. Technology implementation and transfer: [Objectives 1,2,3]
Part 4. Outputs - impact evaluation: [Objectives 1,2,3]



Four-step approach

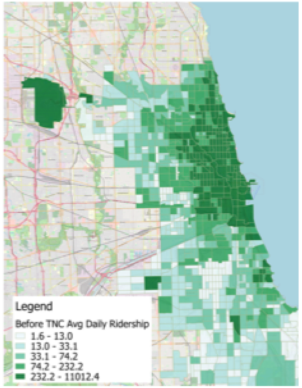
Technical Accomplishments – Part 1 Collected and Shared Data

Data collection

- Socio-demographics data
- Transit system data (e.g. rail and bus lines, stations, routes)
- Spatiotemporal bus, rail, and transportation network companies (TNC) ridership

Data sharing

- Shared data documentation and catalog on Github (https://github.com/sunnyqywang/Chicago-Integrated-Data-Repo.git)



Daily TNC ridership (Pre COVID)

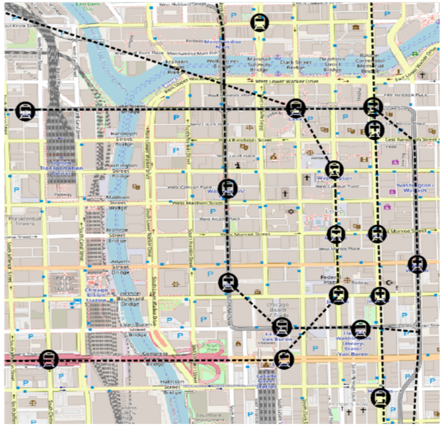
Daily rail ridership (Pre COVID)

Daily bus ridership (Pre COVID)

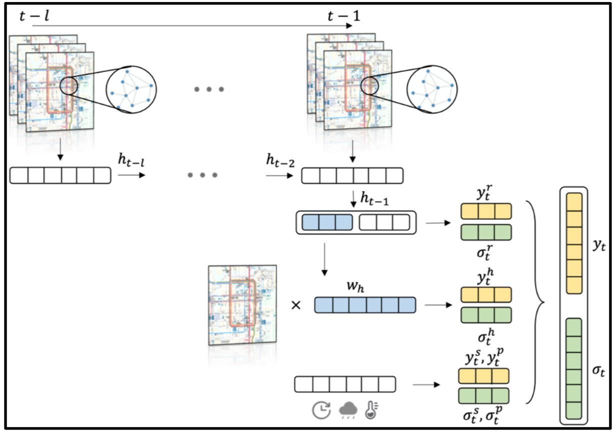
Start — 10/20
12/20
BP1-Milestone 1.3
Completion of Data Collection
NOW
BP1-G/NG — 12/21
BP2-Milestones 2-1/2/3
BP2-G/NG — 12/22
BP2-Milestones 3-1/2/3/4/5
BP3-END — 12/23
Timeline

Technical Accomplishments – Part 2.1 Building Demand Prediction Module with Deep Graphical Neural Networks

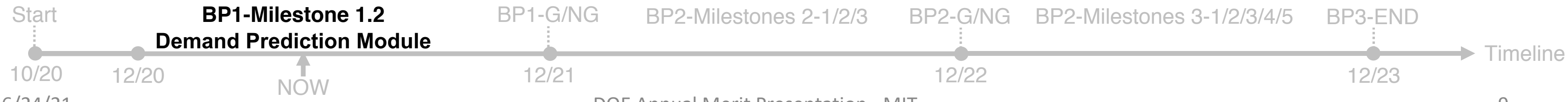
1. Benchmark 1 - Historical observation $y_t = y_{prev}$
2. Benchmark 2 - Weighted least squares $y_t = X_t^m \beta^m + y_{prev}\lambda + \epsilon_t$
3. Deep graphical convolutional neural network



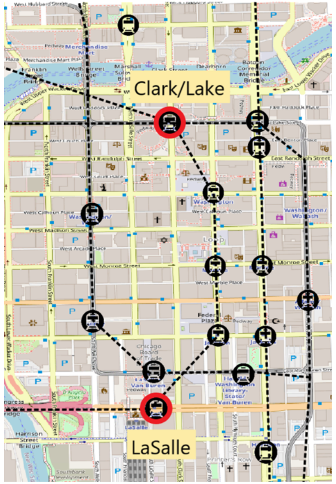
Transit network in Chicago Downtown



Architecture of Graph Neural Networks

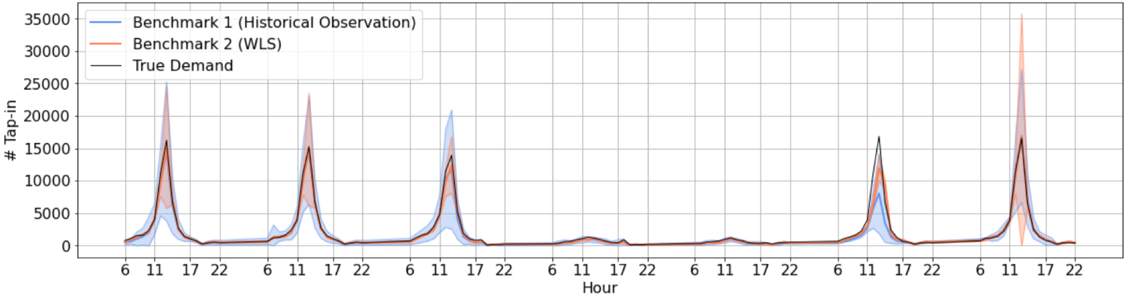


Technical Accomplishments – Part 2.1 Capturing Uncertainty in Travel Demand

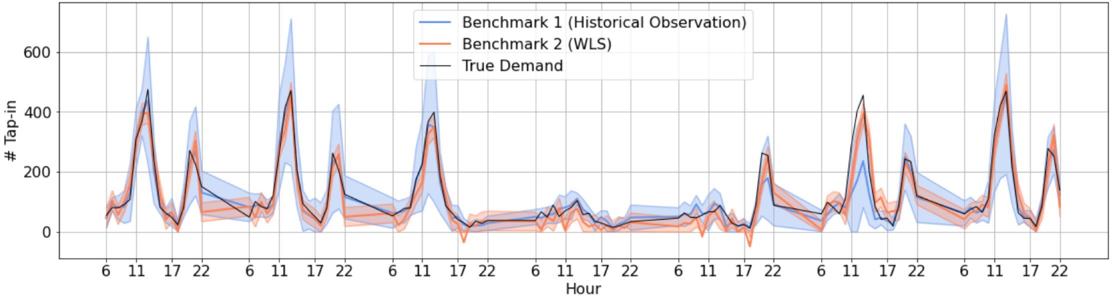


Two Stations in Chicago Downtown

Example 1: Ridership in the Clark station (highest demand)



Example 2: Ridership in the LaSalle station (lowest demand)



Start | **BP1-Milestone 1.2 Demand Prediction Module** | BP1-G/NG | BP2-Milestones 2-1/2/3 | BP2-G/NG | BP2-Milestones 3-1/2/3/4/5 | BP3-END

10/20 | 12/20 | NOW | 12/21 | 12/22 | 12/23 | Timeline

Technical Accomplishments – Part 2.2 Creating Robust Transit Network with Robust Optimization

Formulating the structure of the problem

- Layer 1: Bus operation optimization
- Layer 2: Bus operation optimization with multimodal extension
- Layer 3: Joint network optimization for the multimodal system

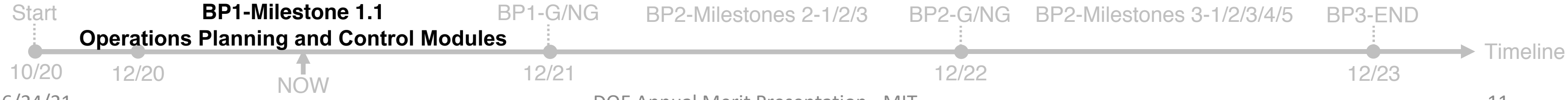
Basic Formulation for bus frequency setting (Layer 1)

Inputs

- Passenger flow (o, d, t): passengers with origin o and destination d departure at time t
- The set of passenger flow $\mathcal{F}$
- Demand matrix $\boldsymbol{u} = (u_t^{o,d})$
- Feasibility set for schedules

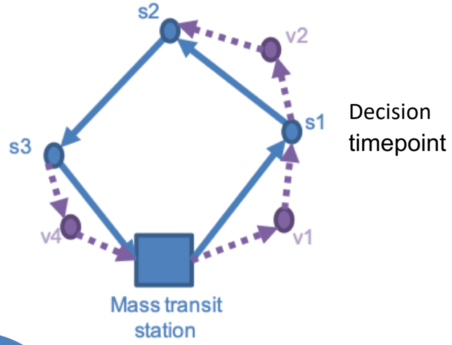
Outputs

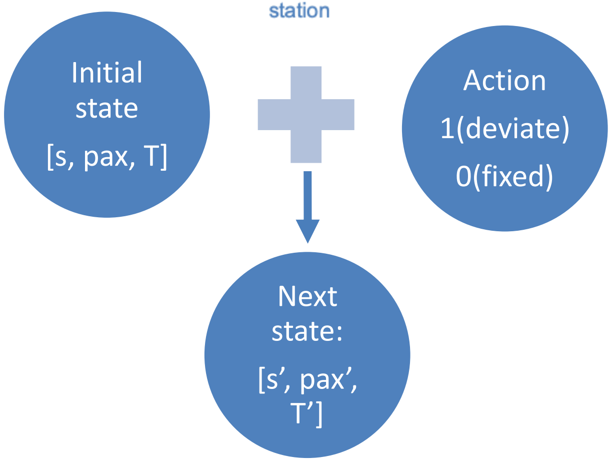
- Decision variables: $\boldsymbol{x} = (x_t^{p,v})$, $x_t^{p,v} = 1$ indicates a vehicle with type v operating on a pattern p departures from the first station at time t, 0 otherwise.



Technical Accomplishments – Part 2.3 Providing Real-Time Bus Feeder Service with Reinforcement Learning

- **Agent:** Buses
- **Environment**: Simulation of the transit service with fixed and flexible routing using estimated demands as inputs
- **Training**: exploring actions that yield the best overall reward (e.g. minimizing delay & service rejection)
- **Result**: Finding the best decision to stay on fixed route vs. deviate in each segment





Start — 10/20
BP1-Milestone 1.1 Operations Planning and Control Modules — 12/20
NOW
BP1-G/NG — 12/21
BP2-Milestones 2-1/2/3
BP2-G/NG — 12/22
BP2-Milestones 3-1/2/3/4/5
BP3-END — 12/23
Timeline

Collaboration and Coordination with Other Institutions

Research partners

- Northeastern University: Collaborated on real-time control strategies and the formulation of RL.
- National Renewable Energy Laboratory: Discussed the computation of MEP metric, data access, and integration of MEP into TSMS.

Transit partners

- Chicago Transit Authority: Collected the bus and rail ridership data with CTA’s support; discussed upcoming survey and planning efforts around first-/last-mile connectivity
- Massachusetts Bay Transportation Authority: Accessed the bus and rail ridership data.

Other potential collaborators

- Argonne National Lab: Discussed POLARIS capabilities and applications
- Boston Seaport TMA: Discussed routing of private shuttles to prepare for field experiments

Remaining Challenges and Barriers – Logistics, Technology, and Implementation

Logistics challenges

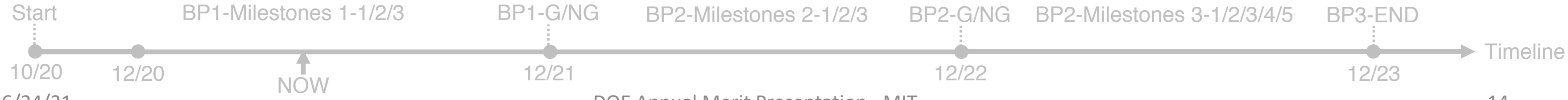
- Two researchers did not complete the FNP until December 2020.
- Two researcher have not completed FNP yet (by May 2021).
- Unfortunately FNP is out of both MIT and DOE's control.
- Need to apply for at least three months' No-Cost Time Extension (NCTE)

Technical challenges

- Uncertainty quantification in DL models
- Analytical solution for the RO formulation under relatively realistic assumptions
- Curse of dimensionality and simulation efficiency in the RL-based real-time bus control

Implementation challenges

- Site choice for field experiment
- Uncertainty in COVID-19 recovery timeline, long-term impacts on partners (e.g. Massport)



Proposed Future Research

1. Data collection
[BP1-Milestone 1.3]

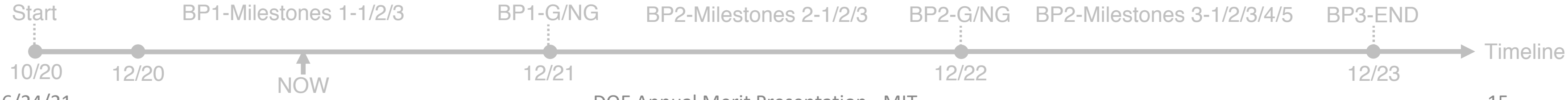
- Collect high-dimensional urban imagery and other essential data for technology development.
- Continue to document and share data.

2. Technology Development
[BP1-Milestone 1.1 and 1.2]

- Create innovative DL models to predict both the mean and variance of travel demand.
- Design bus frequency robust to demand uncertainty and unexpected disruption.
- Design real-time bus control strategies with RL and efficient simulation.

3. Technology Implementation
[BP2-Milestones 2-1/2/3]

- Build the first TSMS integrating the three technology modules.
- Provide an implementation plan for the field experiments.



Summary

Objective

- Build an Integrated TSMS with the state-of-the-art RO, RL, and DL techniques, and demonstrate the benefits in mobility and energy efficiency.

Achievements (January – May, 2020)

- **Logistics & Collaboration**
    - Kicked off the project externally and internally
    - Collaborated with the research and industrial partners for data access and technology development.
- **Technical Accomplishments**
    - Collected and shared socio-economic and real-time ridership data.
    - Constructed benchmark and DL models for the travel demand prediction module.
    - Provided the formulation for transit operation planning and control modules with RO and RL techniques.

Technical Back-Up Slides

Technical Backup Slides – A List of Acronyms

BP: Budget Period

TSMS: Transit-centric Smart Mobility System

DL: Deep Learning

RO: Robust Optimization

RL: Reinforcement Learning

FNP: Foreign National Processing

TNC: Transportation Network Companies

MEP: Mobility-Energy-Productivity

DOE: Department of Energy

NREL: National Renewable Energy Laboratory

NCTE: No-Cost Time Extension

MIT: Massachusetts Institute of Technology

Technical Backup Slides – DL for Demand Prediction

Uncertainty Quantification in Short-term Demand Forecasting

$$y = f(x) + \epsilon$$
$$\epsilon \sim Normal(0, \sigma^2(x))$$

1. Data Uncertainty ($\sigma^2(x)$): The uncertainty (noise) in data. Can be modelled as a function of inputs and quantified by propagating inputs through the neural network and estimate with a likelihood loss.
2. Model Uncertainty: The uncertainty in the estimated model f. Can be quantified with ensemble:
   Take the predicted values ($\mu_1 \ldots \mu_K$) and standard deviations (σ_1 ... σ_K) of top K models, the ensembled mean (μ_*) and standard deviation (σ_*) are

$$\mu_* = \frac{1}{K} \sum_k \mu_k$$

$$\sigma_*^2 = \frac{1}{K} \sum_k (\sigma_k^2 + \mu_k^2) - \mu_*^2$$

Evaluation Metrics

1. Mean: Mean Absolute Error, Root Mean Squared Error, Theil's U
2. Prediction Interval: Prediction Interval Coverage Probability, Mean Prediction Interval Width
3. Composite: Likelihood

Technical Backup Slides – RO for Operation Planning

- Uncertainty in the transit system: Demand uncertainty
- Approach for protecting transit line operation against demand uncertainty: Robust Optimization
- Key component in RO: uncertainty set (model the demand uncertainty in the transit system)
- Feasible transit line operation:

$$\mathcal{X}_B = \{\boldsymbol{x} \in \{0,1\}^{|\mathcal{P}|\times|\mathcal{V}|\times T} : \sum_{p\in\mathcal{P}} \sum_{v\in\mathcal{V}} \sum_{t=1}^{T} c^{p,v} x_t^{p,v} \leq B;\ \sum_{p\in\mathcal{P}} \sum_{v\in\mathcal{V}} x_t^{p,v} \leq 1,\ \forall t = 1, ..., T\}$$

- Nominal (Non-robust) transit line frequency setting model:

$$\min_{\boldsymbol{x}\in\mathcal{X}_B, \boldsymbol{\lambda}} \quad \sum_{(o,d,t)\in\mathcal{F}} \sum_{v\in\mathcal{V}} \sum_{p\in\mathcal{P}^{o,d}} \sum_{\tau=\tau_t^{o,d,p}}^{T} \left(w_{t,\tau}^{o,d,p,v} + \gamma v^{o,d,p}\right) \lambda_{t,\tau}^{o,d,p,v}$$

$$\text{s.t.} \quad L_\tau^{p,v,s} = \sum_{o\in\mathcal{S}_p^{\text{before}}(s)} \sum_{d\in\mathcal{S}_p^{\text{after}}(s)} \sum_{t=1}^{T} \lambda_{t,\tau}^{o,d,p,v} \quad \forall p \in \mathcal{P}, \forall v \in \mathcal{V}, \forall s \in \mathcal{S}_p, \forall \tau = 1, ..., T;$$

$$\sum_{v\in\mathcal{V}} \sum_{p\in\mathcal{P}^{o,d}} \sum_{\tau=\tau_t^{o,d,p}}^{T} \lambda_{t,\tau}^{o,d,p,v} = u_t^{o,d} \quad \forall (o,d,t) \in \mathcal{F};$$

$$L_\tau^{p,v,s} \leq C_p x_\tau^{p,v} \quad \forall p \in \mathcal{P}, \forall v \in \mathcal{V}, \forall s \in \mathcal{S}_p, \forall \tau = 1, ..., T;$$

$$\lambda_{t,\tau}^{o,d,p,v} \geq 0 \quad \forall (o,d,t) \in \mathcal{F}, \forall p \in \mathcal{P}, \forall v \in \mathcal{V}, \forall \tau = 1, ..., T.$$

Technical Backup Slides – RL for Operation Control

Service
- Flexible Feeder service with fixed and deviated stops
- May serve booking requests outside of fixed route
- Expand coverage with minimal LOS impact

System overview
- Control system updated with demand predictions
- Service sends relevant information
- Bus location, load, schedule delay

The Reinforcement Learning approach
- Light simulation model for environment representation
- Offline training for long-term base policy
- Online training for short-term adjustments